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Developing a framework for renewable technology portfolio selection: A case study at a R&D center

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A B S T R A C T

The rapid development of technologies, their increasing complexity and variety, long lead times of R&D and market dynamics have made the task of technology selection difficult. Considering high level of competitiveness, organizations need to strategically allocate their limited resources to the best subset of possible projects.

Today, the increased consumption of energy in modern industrial societies, in addition to the risk of quick exhaustion of fossil resources, has brought about irreversible and threatening environmental changes faced by the world. Dealing with these challenges, decision makers focus on the development of renewable energy technology viewed both as a process of diversification of energy sources and as a creation of an alternative energy option that will help curb down global climate change.

To successfully tackle investment projects in renewable energy, it is essential to use models facilitating decision making process and guarantying the greatest possible value for organizations. Technology portfolio managers have traditionally used consensus-based tools, such as Analytical Hierarchy Process (AHP), Delphi but these tools are limited in their ability to fully quantify the impact of technology portfolio selection on the overall aspects of the system.

This paper presents the results of developing a mathematical model for renewable technology portfolio selection at an oil industry R&D center maximizing support of the organization's strategy and values. The model balances the cost and benefit of the entire portfolio. It is also flexible and changes can be applied very easily.

Contents

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1. Introduction

Today, the problems of energy are considered as topic discussions around the world and a brief look at energy consumption shows that the progress of a country is directly related to it. Nowadays, most of the world's energy is provided by fossil sources, but some problems such as limitations on fossil sources and environmental effects made by using fossil energies has attracted some attention [10].

In developed and developing countries, development of renewable energy technology is viewed both as a process of diversification of energy sources and as a creation of an alternative energy option that will help curb down global climate change and create energy security for the future. Furthermore, this would increase energy supply alternatives for sustainable development and finding a way for better use of fossil fuel resources [10].

The adoption of implementation strategies that will support sustainable development and overcoming barriers that hinder expansion of renewable energy technologies still remains as a big challenge to stakeholders involved in promotion of resources in developing countries. In this respect, developing countries need to re-examine their environmental policy for promotion of renewable energy technologies in order to define its role in revitalization of their economies [10].

With, 9% of the world's oil reserves and 17% of its natural gas reserves, Iran has an abundant supply of fossil fuel resources so its renewable energy consumption was negligible up to now [10]. From now on this trend may be changed and effective energy policy focuses on diversified energy portfolio increasing the security and stability of national power systems. On the one hand, According to the five-year development plan and the modification of energy policies in recent years, renewable energy portion is increasing in total country's energy portfolio. On the other hand, Iran has a total territorial area of 1,648,000 km^2 and it is located a geographical zone having high renewable energy potential.

There are several criteria considered while constructing an energy portfolio. One of these criteria is technology. This includes factors such as scale of technology (e.g., wind power or geothermal), efficiency, infrastructures, product designs, and standards. Industrial and academic interest in how to more effectively manage technology is growing as the complexity, cost and rate of technological innovation increase. In other words, having the best technology doesn't guarantee success anymore; but it has to be in the support of technology strategies of the company.

A technology strategy is a particular generation of an organization's overall objectives, principles and tactics relating to the technologies that the organization uses. It explains how technology should be utilized as part of an organization's overall corporate strategy [2].

The main concept of technology portfolio is to allocate a limited set of resources to projects in a way that balances risk, reward, and is in alignment with corporate strategy [3].

To tackle an investment project in renewable energies that is subject to risks regarding prices in an energy market, and the investment and operating costs among others [11], it is necessary to hedge against these risks by seeking the greatest possible return. A good investment portfolio must diversify its risk [12].

The initial method developed to organize the investment decisions of financial portfolios is based on mean–variance model put forward by Markowitz in 1952. It assists in the selection of the most efficient portfolio based on expected returns (mean) and the standard deviation (variance) of the various portfolios [13–15]. Applications of this concept to energy investment where risks are considered can be seen in [16–19]. Yu [20] presents a model to assess risks in a multi-pool setting. A comprehensive review of the state-of-the-art in energy portfolio can be found in Kienzle et al. [21].

Furthermore, some complicated models were developed to deal with actual nature of technology and R&D project selection. Dickinson et al. [3] developed a nonlinear, integer programming model, using a dependency Matrix which quantifies the inter dependencies between projects, to optimize project selection in the Boeing Company. Smith et al. [8] used a multi-criteria decision making approach to search all possible portfolios for the maximum science value within budget constraints of Mars exploration program. The scientific value of each portfolio was used to compute each portfolio contribution to a strategic exploration goal. Elfes et al. [5] used a decision theory approach to support strategic decision-makers within NASA.

Heidenberger et al. break quantitative technology portfolio selection methods in R&D centers into six categories [6]: (1) benefit measurement methods arranging projects according to the benefit they provide within overall budget constraints; (2) mathematical programming optimizing the expected benefits to be realized from a portfolio of R&D projects, while recognizing limits to the available resources; (3) decision and game theory which takes into account uncertain future events or firm's reactions to environmental changes; (4) simulation models representing real world systems and usually used when experiments cannot be applied in real world because of cost or time; (5) heuristics finding acceptable but not necessarily optimal answers for problems with high degree of complexity; (6) cognitive emulation using pervious experiences to help decision making processes.

Reviewing related literature reveals that it is essential to use models and approaches that best fit the operating method of the company. As Braunstein [4] pointed out, the applied approach should link the corporate goals and strategy to its major functional units.

In this paper, benefit measurement models, mathematical programming and heuristic modeling are used to provide a framework to select the best possible portfolio of projects related to renewable technology development in R&D centers. The optimization model identifies the funding strategy that maximizes the support of the strategy, subject to budgetary and portfolio balance constraints such as expected timeline and schedule of investment, strategic requirements, magnitude of portfolio, and relationship or interdependencies with other projects in the portfolio. The model selects if, and when, to start funding a project over a scheduling period. The effectiveness of a project is influenced by whether or not it is in alignment with the overall strategy in the organization.

This paper is organized as follows. Section 2 deals with appropriate criteria of technology portfolio evaluation in R&D center of renewable energy. A mathematical programming model of renewable technology portfolio selection is developed in Section 3. In Section 4, the methods and the computational results of problem solving are presented. Finally, the conclusions derived from the analysis of renewable technology portfolio selection are presented.

2. Technology portfolio evaluation framework

According to [7], technology portfolio provides decision makers with the definition of a clear dichotomy between two families of elements: (1) competitiveness and (2) attractiveness. "The company's technological competitiveness" is the elements mainly under the firm's control and depends on the firm's behavior and decisions. "The attractiveness of the technology" does not depend on the firm's actions and is beyond its control.

Assessing the situation of a firm regarding these factors is also useful for strategy formulation because they offer guidance to the resource allocation process [7].

Table 1
List of important factors in technology selection.

Market	**Capability**
Span of applications opened by technology (*app*)	Alignment with organization objective and capability (*stra o*)
Potential of commercialization (*comm.*)	Value of laboratories (*personnel*)
Supporting national related strategies (*stra*)	Successful Experience accumulated in the field (*exp*)
Competitiveness	Registered patents (*patents*)
Key of technology (*key*)	Value of equipments (*equip*)
Competitive situation in market (*situation*)	**Environmental factors**
Added value (*Added value*)	Impact on environmental factors and energy consumption improvement (*env*)
Technical factors	
Position of the technology in its own life-cycle (*life-cycle*)	
Threat of substitution technologies (*subs*)	
Ability to result in technical Know-How (*Know-How*)	
Ability to use international cooperation potentials (*international*)	

We use a theoretical approach, which is based on analytic hierarchy process (AHP) to help in renewable technology project selections. Analytic Hierarchy Process [22] is one of the most popular and powerful methods for group decision-making used in *p* selection [23]. AHP is a useful approach for evaluating complex multiple criteria alternatives involving subjective judgment.

2.1. Building the hierarchy model and its criteria

Evaluating renewable technology portfolio based on criteria drawn out of related literature, we initially developed a hierarchy model of renewable technology portfolio selection based on the criteria and related sub-criteria. Fig. 1 and Table 1 show the primary list of these criteria and sub-criteria.

The primary list should be revised and changed based on the organization's culture and special needs. Some sub-criteria may be added to list and some of them may be considered as unimportant and be eliminated. We asked experts from different areas of renewable energy technology to review the hierarchy model.

2.2. Weights of evaluation criteria

Once the hierarchy model is completed, the company should determine importance of each factor regarding the strategy of the organization. The acceptable results can be achieved by the help of panel of experts in the related field. So, the above mentioned experts were asked to complete a questionnaire by pair-wise comparing the relative importance of criteria using a scale from 1 to 9. A decision-maker determines his or her weights by conducting pair-wise comparisons between criteria. We first use linguistic terms to represent the experts' assessments. For example, experts use 9 for "extremely important", 5 for "relatively important", and 1 for "extremely unimportant" for criteria.

We analyzed their subjective judgments by ExpertChoice. If the subjective judgments of the experts were inconsistent, we asked them to repeat the pair-wise comparison processes until the consistency index was less than 0.1.

2.3. Overall importance of criteria and sub-criteria

After combining the priorities over all hierarchy, overall importance weights of criteria and sub-criteria were determined. The resulted weights are summarized Figs. 2 and 3.

Finally, ten most important factors, according the computed weights, were selected to be used in the final model (Table 2).

3. Renewable technology portfolio selection mathematical model

The next step is to provide optimization model that integrates the portfolio management's existing tools into a linear, integer program. The model incorporates data from the experts and the estimated financial performance calculating the total performance

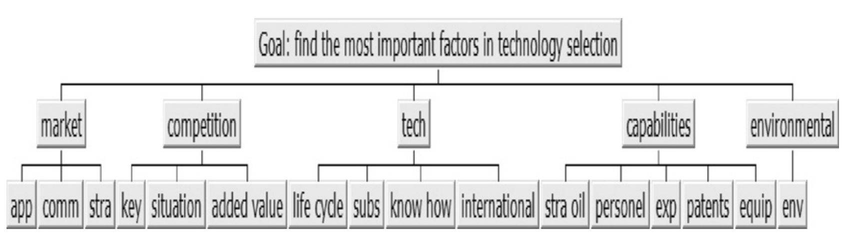

Fig. 1. The developed hierarchy model of renewable technology portfolio evaluation criteria.

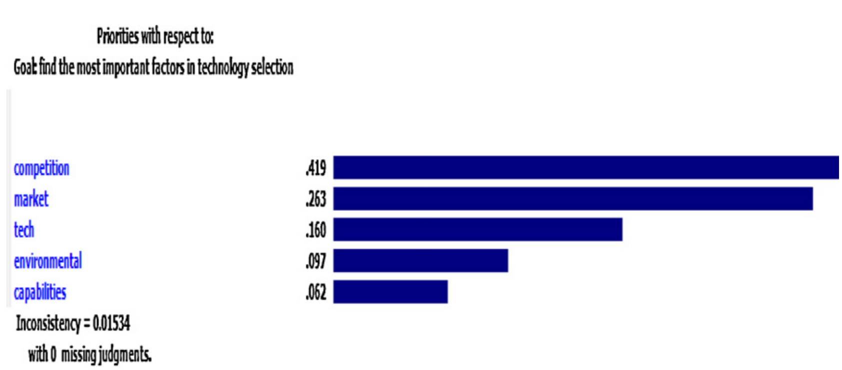

Fig. 2. Criteria relative importance.

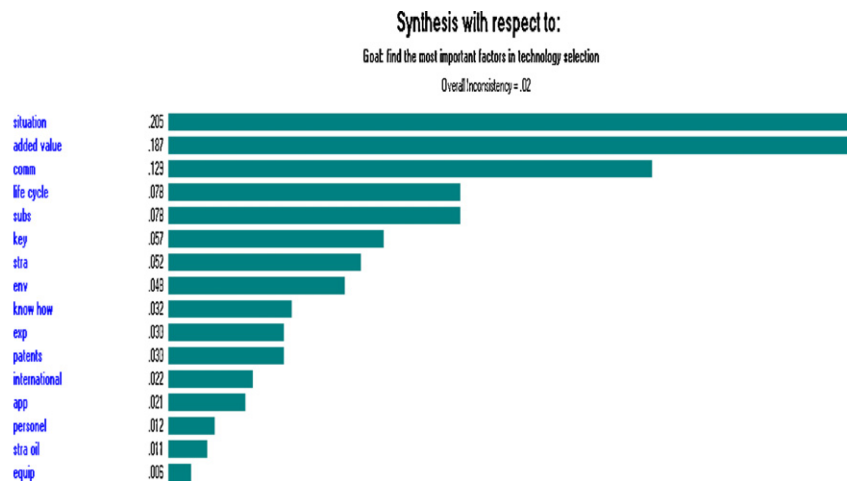

Fig. 3. Prioritizing sub-criteria.

of portfolio. The optimization model then maximizes the estimated support of firm's strategy thorough technology competitiveness and attractiveness provided with portfolio, subject to portfolio balance and budget constraints.

The renewable energy technology portfolio selection problem is to select a set of projects from a pool of candidate projects to maximize the expected values during the planning horizon. Each candidate project has specific duration and its execution requires the exclusive use of a number of resources (e.g., budget, human resources, etc.). However, the availability of each resource type is usually limited. Unlike money, there is limited transferability for human resources from one project to another project, due to the specialization of R&D skills. To effectively utilize limited resources, it is important to link portfolio selection decisions to the key corporate strategies and to maintain the balance of R&D project portfolio [9].

x_{itj} is the binary decision variable of problem which is take the amount of 1 if the project *i* starts receiving fund in year *j*, where *j* is equal or less than *t* (the current year of planning horizon), otherwise $x_{itj} = 0$.

3.1. Model constraints

Timing: $x_{it,j}$ is the decision variable, *i* is the project index, *t* is the enumerated year in the planning horizon (from year 1 to year *n*) and *j* is the year in which a project starts receiving fund. The project can only be started once. To model this constraint, another binary variable, y_i, is presented in which $y_i = 1$ when project *i* is slated to receive funding in calendar years and is subject to the constraint:

$$\sum_{t=1}^{n}\sum_{j=1}^{t} x_{itj} = y_i \quad i = 1, 2, \ldots, p \tag{1}$$

$$y_i \leq 1 \quad i = 1, 2, \ldots, p \tag{2}$$

Portfolio size: There may be some restrictions according to limited human resources to number of projects to be selected in calendar years. This number is usually estimated by experts and it is based on previous experiences.

$$\sum_{i=1}^{p} y_i \leq Q \tag{3}$$

Table 2
Final sub-criteria used in technology portfolio selection according to AHP results.

Criteria/sub-criteria	Relative priority	Relative weight	Criteria/sub-criteria	Relative priority	Relative weight
Market	2	0.263	**Capability**	5	0.062
Span of applications opened by technology (*app*)	13	0.21	Alignment with organization objective and capability (*stra o*)	15	0.11
Potential of commercialization (*comm.*)	3	0.129	Value of laboratories (*personnel*)	14	0.12
Supporting national related strategies (*stra*)	7	0.52	Successful Experience accumulated in the field (*exp*)	10	0.30
Competitiveness	1	0.419	Registered patents (*patents*)	11	0.30
Key of technology (*key*)	6	0.57	Value of equipments (*equip*)	16	0.06
Competitive situation in market (*situation*)	1	0.205	**Environmental factors**	4	0.097
Added value (*Added value*)	2	0.187	Impact on environmental factors and energy consumption improvement (*env*)	8	0.48
Technical factors	3	0.160			
Position of the technology in its own life-cycle (*life-cycle*)	4	0.78			
Threat of substitution technologies (*subs*)	5	0.78			
Ability to result in technical Know-How (*Know-How*)	9	0.32			
Ability to use international cooperation potentials (*international*)	12	0.22			

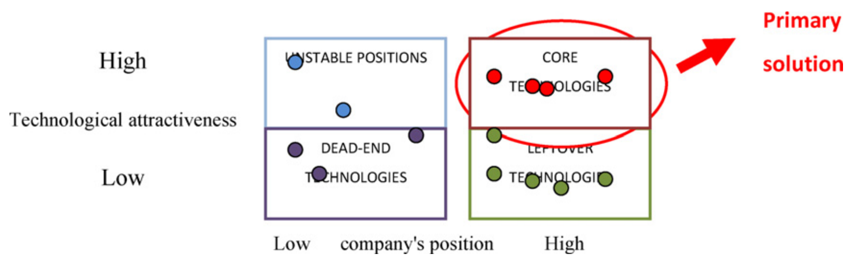

Fig. 4. Technology portfolio models.

Portfolio cost: A total yearly cost includes capital expenditures, the cost of implementation and sustaining costs. It is assumed that cost is dependent of the year in which a project is launched. The project costs for the entire portfolio are captured in a matrix where each element represents the incremental cost of project related to implementation phase of project, which is based on number of years spent since start of the project. This matrix is based on the predicted costs. The budget represents the maximum amount of money available to spend on the portfolio of projects for each calendar year. The cost in any given year cannot exceed the budget available.

$$\sum_{i=1}^{p}\sum_{j=1}^{t} C_{i(t-j+1)}x_{itj} \le B_t \quad t = 1, 2, \ldots, n \tag{4}$$

where $C_{i(t-j+1)}$ is the predicted cost of project i from its start date through the current year.

Strategic requirements: This constraint sets the number of projects that must support each of the strategic objectives (M_m). N_{im} is a matrix that each element of it is equal to one if project i supports objective m.

$$\sum_{i=1}^{p} N_{im}y_i \ge M \tag{5}$$

Dependency: The last constraint is focused on the prerequisite rules and dependencies between projects. P is a matrix in which $p_{ij} = 1$ where project i is dependent to project j, and if project i is selected then project j should be selected too.

$$y_i \ge p_{ij}y_i \quad i, j = 1, 2, \ldots, p \tag{6}$$

3.2. Model objective function

The relative importance weights of criteria and sub-criteria were determined in previous section. In this section we use those sub-criteria and their relative weights to calculate the selected portfolio support of firm's strategy (sup) as model objective function:

$$\max \sum_{i=1}^{p} \text{sup}_i \cdot y_i \tag{7}$$

$$\text{sup}_i = \sum_{k=1}^{10} W_k S_{ik}, \quad i = 1, 2, \ldots, p \tag{8}$$

where w_k shows the weight of the kth sub-criterion and S_{ik} is the representative of the ith technology score in relation to the kth sub-criterion.

4. Problem solving and computational results

The optimization model may be solved by any mathematical method and tools such as solver, lingo or heuristic methods regarding the size of the problem. As the size of the problem increases, the search-space of candidate solutions grows exponentially which makes an exhaustive search for the optimal solution inadequate regarding time and cost, but exact methods may be used when the size of the problem is small.

In this research Tabu search and simulated annealing algorithms were developed to solve the optimization model. Decision makers can easily and quickly use these programs and update them over time periods.

Both algorithms need a primary solution. Starting from a good primary solution would improve the quality of the algorithm. In this case a primary (but not necessarily feasible) solution may be achieved by the help of attractiveness via company's position matrix [7].

If the strategy of company is based on competition, core technologies are selected and if it is resource based, leftover technologies could be selected as a primary solution. Fig. 4 is a sample of application of this matrix.

In order to verify Tabu search and Simulated Annealing algorithms, the test problems were classified into two main groups based on their size:

- Small size problems;
- Medium and large size problems.

Lingo was used to solve small size problems. The results then compared to the results achieved by using Tabu search and Simulated Annealing algorithms, it seems that both algorithms result in optimal solution in small size problems.

In medium and large size problems, the optimization model cannot be solved in polynomial time, so linear programming relaxation method was used to get information about the original problem. The linear programming relaxation of a 0–1 integer program is the problem that arises by replacing the constraint that each variable must be 0 or 1 by a weaker constraint, that each variable belong to the interval [0,1].

$$x_i \in \{0, 1\} \rightarrow 0 \le x_i \le 1 \tag{9}$$

The resulting relaxation is a linear program. In all cases, the solution quality of the linear program is at least as good as that of the integer program, because any integer program solution would also be a valid linear program solution. That is, in a maximization problem, the relaxed program has a value greater than or equal to that of the original program (upper bound) [1]. So the difference between the best solution achieved by two algorithms and the upper bound can be calculated as the percentage of error for each problem. The results of sixteen test problems are summarized in Table 3.

Analyzing the percentage of error shows that the quality of solution achieved by Tabu Search algorithm is usually better than those of Simulated Annealing algorithm. Despite the fact that it takes longer for Tabu Search algorithm to solve the problem than Simulated Annealing algorithm, it seems that Tabu Search algorithm achieves better results in a quite short time even in large size problems. Figs. 5 and 6 show the comparisons between two algorithms according to run times and the percentage of error respectively.

Table 3
Results of test problem.

		Tabu search		Simulated annealing		lingo	Upper bound	Percentage of error	
		Best solution	Run time	Best solution	Run time			T.S.	S.A.
#1	$n=4$ $p=5$	1.9201	0.003669	1.9201	1.021083	1.9201	–	0.0000	0.0000
#2	$n=4$ $p=7$	2.0859	0.005074	2.0859	1.039387	2.0859	–	0.0000	0.0000
#3	$n=4$ $p=10$	3.0043	0.007108	3.0043	1.041962	3.0043	–	0.0000	0.0000
#4	$n=4$ $p=15$	3.2650	0.008918	3.2650	1.092730	3.2650	–	0.0000	0.0000
#5	$n=4$ $p=20$	3.8769	3.3105	3.7918	4.55868	–	3.9502	1.855602	4.00992
#6	$n=5$ $p=10$	3.1283	0.008493	3.1283	1.92292	3.1283	–	0.0000	0.0000
#7	$n=5$ $p=15$	3.7612	5.7384	3.6382	5.19394	–	3.8069	1.200452	4.431427
#8	$n=5$ $p=20$	3.7935	11.0604	3.7291	6.56717	–	3.8964	2.640899	4.293707
#9	$n=5$ $p=25$	4.4202	11.5203	4.3543	6.82858	–	4.5366	2.565798	4.018428
#10	$n=5$ $p=30$	4.4831	17.1393	4.3736	7.41518	–	4.5708	1.918701	4.314343
#11	$n=5$ $p=35$	4.8604	19.2843	4.6327	7.67547	–	4.9184	1.179245	5.8088
#12	$n=5$ $p=40$	5.2880	22.5413	5.0047	9.07499	–	5.3719	1.561831	6.83557
#13	$n=5$ $p=45$	5.9933	30.1813	5.6686	10.31608	–	6.1058	1.84251	7.160405
#14	$n=5$ $p=50$	6.233	36.27433	5.8739	10.60857	––	6.93	10.06	15.24
#15	$n=10$ $p=10$	3.8474	7.35199	3.7224	4.77098	–	4.0281	4.486	7.5892
#16	$n=10$ $p=15$	4.8176	41.63098	4.4961	21.10759	–	5.0216	4.06	10.46

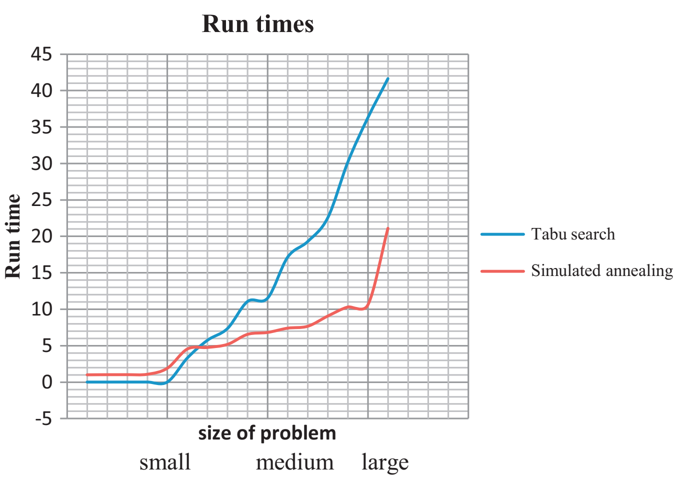

Fig. 5. Run times of Tabu search and simulated annealing algorithms.

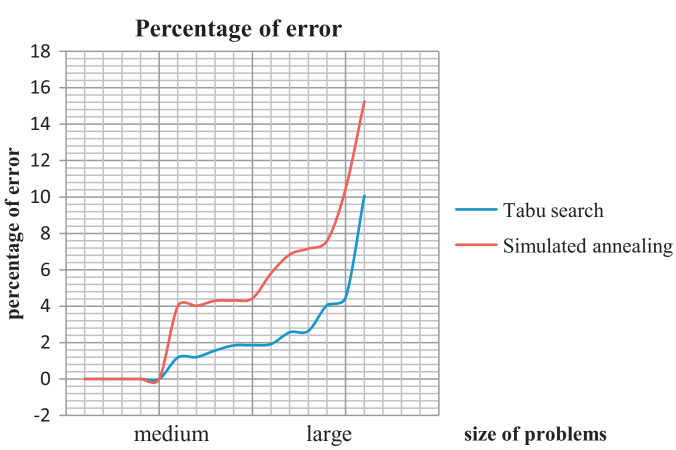

Fig. 6. Percentage of error of Tabu search and simulated annealing algorithms.

5. Conclusion

The contribution of renewable energy to the total energy mix is still small, due to lack of knowledge about their potential and insufficient social and environmental policies and programs to encourage their use/implementation. The diffusion of renewable energy technologies has been hampered by lack of efficient management, maintenance and capacity to construct and purchase the right technology portfolio.

This work proposes a quantitative method that enables a team to evaluate and optimize a renewable energy technology portfolio where the projects are dependant and the cost of implementation is highly related to the phase of implementation.

The optimization model utilizes existing data and integrates the existing portfolio management tools. The model's format provides flexibility to evaluate performance of alternative solutions. The mathematical nature of the model requires the input data to be numerically quantifiable. Many optimization models have been criticized in the past because they rely too heavily on financial data that is neither available nor very accurate [3].

In this method, the data predictions do not have to be precise, but their relative ranges do have to be consistently applied. However, it does matter that the experts agree on the general magnitude and that the values within the model are judged on the same relative scale.

The model can quickly answer some questions about addition of new projects or changes of amount of budget. The model also minimizes the time required to evaluate the portfolio or re-evaluate it when project metrics were updated. Finally the model balances the portfolio in alignment with the overall objectives of the company. The model effectively provides a means to optimize and balance projects over multiple periods in a technology portfolio.

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